An NLP Framework for Measuring Job Competencies

Dissertation Project

MSc in Big Data Analytics and Artificial Intelligence

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Load the data

The main datafile contains text responses from job applicants and evaluation ratings provided by humans. Additionally, a BARS was created and the text from this is also loaded.

```
!python --version
```

```
Python 3.10.12
```

```
pip install POT
```

```
Collecting POT
  Downloading POT-0.9.1-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (789 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 790.0/790.0 kB 10.9 MB/s eta 0:00:00
Requirement already satisfied: numpy>=1.16 in /usr/local/lib/python3.10/dist-packages (from POT) (1.23.5)
Requirement already satisfied: scipy>=1.0 in /usr/local/lib/python3.10/dist-packages (from POT) (1.11.4)
Installing collected packages: POT
Successfully installed POT-0.9.1
```

```
import pandas as pd

file_path = "/content/drive/MyDrive/ATU course/dissertation/"
original_data = pd.read_csv(f"{file_path}job_simulation_responses.csv")
bars_text = pd.read_csv(f"{file_path}BARS_v2.0.csv")
```

```
original_data
```

response_id rating_chooses_appropriate_action rating_commits_to_actic

bars_text

	subcompetency	bars_high	bars_low
0	gathers_information	Effectively and proactively gathers comprehens...	Gathers irrelevant data. Does not seek multipl...
1	interprets_information	Accurately interprets the information availabl...	Misinterprets the available information genera...
2	identifies_issues_and_opportunities	Generates a range of viable options. Proactive...	Misses opportunities. Fails to consider the co...
3	includes_others	Seeks input from other stakeholders to incorpo...	Excludes others from decision-making. Does not

Data cleaning

1. Removing question prompts.

There are some repeated strings in the text which provided structure to the exercise or gave specific questions for them to answer. These are not part of the responses. For example "*What were the three most important and the three least important e-mails to handle?*"

These repeated strings are removed to leave only the respondent's text to be used in the analysis.

```
# Create a dictionary containing the strings to be removed

remove_dict = {
    "remove_pattern_1": r'Original Message----- From: Assessment Administrator Sent:.*?Cc:',
    "remove_pattern_2": r'Subject : RESPONSE REQUIRED: About your day',
    "remove_pattern_3": r'This e-mail contains some final questions for you. Your answers to these questions will help in th
    "remove_pattern_4": r'1. Please list the major categories of issues or problems facing Customer Service Team 5 of Soundp
    "remove_pattern_5": r'2. What were the three most important messages you considered the highest priorities to handle\? W
    "remove_pattern_6": r'3. List specific examples \(if any\) of instances where you detected a relationship between two of
    "remove_pattern_7": r'For example, when you decided how respond to one message, did you consider information provided nc
    "remove_pattern_8": r'4. Describe what additional information you would have liked to have in order to have a better or
    "remove_pattern_10": r'The messages you received today included:  Weedler Contracting: A customer is suspected of abusir
    "remove_pattern_11": r'Eluto Caplanu: Someone has placed an insulting message on Elutos lunch',
    "remove_pattern_12": r'Effective mentoring pays dividends: Taylor mentored Jerry Winters and presents the results',
    "remove_pattern_13": r'Customer satisfaction insights: Tracy Hurdle reports research on customer satisfaction',
    "remove_pattern_14": r'Promotion: There is new room in the budget to promote a part-time employee to full-time',
    "remove_pattern_15": r'Professional conduct: A salesperson complains that representatives behave unprofessionally',
    "remove_pattern_16": r'Theft of company-confidential information: A security guard suspects an associate of improper act
    "remove_pattern_17": r'Bench strength: Representatives must be signed up for training per company policy',
    "remove_pattern_18": r'quietPAPER ONE: A new product is faulty and will start to produce complaints in two weeks',
    "remove_pattern_19": r'Paperless office: A plan is presented to replace paper files',
    "remove_pattern_20": r'Installation in Sales: Sales requests scheduling soundproofing for their area, and a meeting with
    "remove_pattern_21": r'Feedback process: Kim proposes a way to efficiently deal with customer feedback',
    "remove_pattern_22": r'Fletcher Systems: An unhappy customer demands reinstallation and a meeting',
    "remove_pattern_23": r'Subject : About your day \(1 of 2\)',
    "remove_pattern_24": r'This e-mail and the one that follows contain some final questions for you.',
    "remove_pattern_25": r'Your answers to these questions will help us evaluate your performance by giving us a better unde
    "remove_pattern_26": r'It is therefore very important that you provide complete and thorough answers to the questions be
    "remove_pattern_27": r'To reply to the questions in these messages, simply click the Reply button above and enter your r
    "remove_pattern_28": r'1. Did you handle each challenge in the order you received it, or did you handle them another way
    "remove_pattern_29": r'2. Please list the major categories of issues or problems facing Final Assembly in the Bridgeport
    "remove_pattern_30": r'3. Describe why each entry in Question 2 is an issue or problem.',
    "remove_pattern_31": r'Subject : About your day \(2 of 2\)',
    "remove_pattern_32": r'Following are some of the e-mails that you received today, along with some questions about how yc
    "remove_pattern_33": r'Your answers to these questions will help us evaluate your performance by giving us a better unde
    "remove_pattern_34": r'To respond, simply click the Reply button above and enter your answers in the form of a reply e-m
    "remove_pattern_35": r'1. What were the three most important and the three least important e-mails to handle\?',
    "remove_pattern_36": r'2. Why did you feel that the e-mails you rated as most important were critical\?',
    "remove_pattern_37": r'3.Todays assessment provided you with background information about Soundproof Solutions and also
    "remove_pattern_38": r'Were there situations where information from one source/challenge helped you to better understanc
    "remove_pattern_39": r'If so, please list specific examples of theseinstances \(Example: Message X related to Message Z,
}


# Convert all the text exercise columns to string

cols = original_data.columns[original_data.columns.str.contains('text_exercise_')]
data = original_data.copy() # create a copy of the original data
data[cols] = data[cols].fillna('')
data[cols] = data[cols].astype(str)
```

```
# Replace "$0" with an empty string in the specified columns
data[cols] = data[cols].applymap(lambda x: str(x).replace('$0', ' '))


import re

# Function to remove strings
def remove_strings_func(text, patterns):
    for name, pattern in patterns.items():
        text = re.sub(pattern, '', text)
    return text

# Apply the function to remove strings
data['text_exercise_final_clean'] = data['text_exercise_final'].apply(lambda x: remove_strings_func(x, remove_dict))
```

2. Spelling correction

The programme used to collect or process the responses from participants inadvertently concatenated words together in many cases. Additionally, respondents made spelling mistakes.

The text data was processed to split concatenated words and autocorrect spelling.

```
!apt-get install aspell
!apt-get install libaspell-dev
!pip install aspell-python-py3
!pip install wordninja
```

```
Reading package lists... Done
Building dependency tree... Done
Reading state information... Done
The following additional packages will be installed:
  aspell-en dictionaries-common libaspell15 libtext-iconv-perl
Suggested packages:
  aspell-doc spellutils wordlist
The following NEW packages will be installed:
  aspell aspell-en dictionaries-common libaspell15 libtext-iconv-perl
0 upgraded, 5 newly installed, 0 to remove and 15 not upgraded.
Need to get 911 kB of archives.
After this operation, 3,823 kB of additional disk space will be used.
Get:1 http://archive.ubuntu.com/ubuntu jammy/main amd64 libtext-iconv-perl amd64 1.7-7build3 [14.3 kB]
Get:2 http://archive.ubuntu.com/ubuntu jammy/main amd64 libaspell15 amd64 0.60.8-4build1 [325 kB]
Get:3 http://archive.ubuntu.com/ubuntu jammy/main amd64 dictionaries-common all 1.28.14 [185 kB]
Get:4 http://archive.ubuntu.com/ubuntu jammy/main amd64 aspell amd64 0.60.8-4build1 [87.7 kB]
Get:5 http://archive.ubuntu.com/ubuntu jammy/main amd64 aspell-en all 2018.04.16-0-1 [299 kB]
Fetched 911 kB in 0s (2,397 kB/s)
Preconfiguring packages ...
Selecting previously unselected package libtext-iconv-perl.
(Reading database ... 120882 files and directories currently installed.)
Preparing to unpack .../libtext-iconv-perl_1.7-7build3_amd64.deb ...
Unpacking libtext-iconv-perl (1.7-7build3) ...
Selecting previously unselected package libaspell15:amd64.
Preparing to unpack .../libaspell15_0.60.8-4build1_amd64.deb ...
Unpacking libaspell15:amd64 (0.60.8-4build1) ...
Selecting previously unselected package dictionaries-common.
Preparing to unpack .../dictionaries-common_1.28.14_all.deb ...
Adding 'diversion of /usr/share/dict/words to /usr/share/dict/words.pre-dictionaries-common by dictionaries-common'
Unpacking dictionaries-common (1.28.14) ...
Selecting previously unselected package aspell.
Preparing to unpack .../aspell_0.60.8-4build1_amd64.deb ...
Unpacking aspell (0.60.8-4build1) ...
Selecting previously unselected package aspell-en.
Preparing to unpack .../aspell-en_2018.04.16-0-1_all.deb ...
Unpacking aspell-en (2018.04.16-0-1) ...
Setting up libtext-iconv-perl (1.7-7build3) ...
Setting up dictionaries-common (1.28.14) ...
Setting up libaspell15:amd64 (0.60.8-4build1) ...
Setting up aspell (0.60.8-4build1) ...
Setting up aspell-en (2018.04.16-0-1) ...
Processing triggers for libc-bin (2.35-0ubuntu3.4) ...
/sbin/ldconfig.real: /usr/local/lib/libtbbbind.so.3 is not a symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbbbind_2_5.so.3 is not a symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbbmalloc_proxy.so.2 is not a symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbbmalloc.so.2 is not a symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbbbind_2_0.so.3 is not a symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbb.so.12 is not a symbolic link

Processing triggers for man-db (2.10.2-1) ...
Processing triggers for dictionaries-common (1.28.14) ...
aspell-autobuildhash: processing: en [en-common].
```

```
import wordninja
import aspell

# Create an Aspell object
spell_checker = aspell.Speller()

# function to autocorrect and split concatenations
def correct_spelling_and_split(text):
    # Use regular expression to separate words from punctuation
    words_with_punctuation = re.findall(r"[\w]+|[^\w\s]", text)

    corrected_words = []

    for word_with_punctuation in words_with_punctuation:
        # Check if the word is recognised by aspell
        if not spell_checker.check(word_with_punctuation):
            # If not recognised, split the word using wordninja
            split_words = wordninja.split(word_with_punctuation)

            # If all split words are recognised, add them to corrected words
            if all(spell_checker.check(word) for word in split_words):
                corrected_words.extend(split_words)
            else:
                # If any split word is not recognised, use aspell suggestion on the original unsplit word
                suggestions = spell_checker.suggest(word_with_punctuation)
                # if there are no suggestions, keep original
                suggestion = suggestions[0] if suggestions else word_with_punctuation
                corrected_words.append(suggestion)
        else:
            # If the word is recognised, add it to corrected words
            corrected_words.append(word_with_punctuation)

    # Join corrected words back into a string
    corrected_text = ' '.join(corrected_words)

    return corrected_text

# Example usage
text_to_correct = "opportunitycost interestnig feijekkepejekfeskt"
corrected_text = correct_spelling_and_split(text_to_correct)
print(corrected_text)
```

```
opportunity cost interesting feijekkepejekfeskt
```

Combine all text data into one column.

```
data.columns
```

```
Index(['response_id', 'rating_chooses_appropriate_action',
       'rating_commits_to_action', 'rating_gathers_information',
       'rating_identifies_issues_opportunities',
       'rating_interprets_information', 'rating_involves_others',
       'rating_decision_making_final_score', 'text_exercise_4',
       'text_exercise_5', 'text_exercise_6', 'text_exercise_7',
       'text_exercise_8', 'text_exercise_9', 'text_exercise_10',
       'text_exercise_11', 'text_exercise_12', 'text_exercise_13',
       'text_exercise_14', 'text_exercise_15', 'text_exercise_16',
       'text_exercise_17', 'text_exercise_18', 'text_exercise_19',
       'text_exercise_final', 'text_exercise_final_clean'],
      dtype='object')
```

```
cols = data.columns[data.columns.str.contains('text_exercise_')]
cols = [col for col in cols if col != "text_exercise_final"]
```

```
data["all_text"] = data[cols].apply(lambda x: ''.join(x), axis=1)
```

```
data["all_text_clean"] = data["all_text"].apply(correct_spelling_and_split)
```

3. Tokenise text and remove stopwords

Convert text data to lowercase, remove punctuation, perform tokenisation, and remove English stopwords using NLTK library.

```
import nltk
from nltk.corpus import stopwords
nltk.download('stopwords')

# Function to remove stopwords from a list of tokens
def remove_stopwords(token_list):
    stop_words = set(stopwords.words('english'))
    filtered_tokens = [word for word in token_list if word not in stop_words]
    return filtered_tokens
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
import string

# Function to remove punctuation from a list of tokens
def remove_punctuation_from_tokens(tokens):
    punctuations = set(string.punctuation)
    filtered_tokens = [token for token in tokens if token not in punctuations]
    return filtered_tokens
```

```
from nltk.tokenize import word_tokenize
nltk.download('punkt')

# Data processing pipeline function
def data_cleaning_pipeline(text):
    text = text.lower()
    tokens = word_tokenize(text)
    tokens = remove_punctuation_from_tokens(tokens)
    tokens = remove_stopwords(tokens)
    return tokens
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
```

```
# Apply the data cleaning pipeline

# Target text
target_text = bars_text['bars_high'].str.cat(sep=' ')
target_text_tokens = data_cleaning_pipeline(target_text)

# Response text
data['tokenized_text'] = data['all_text_clean'].apply(data_cleaning_pipeline)
```

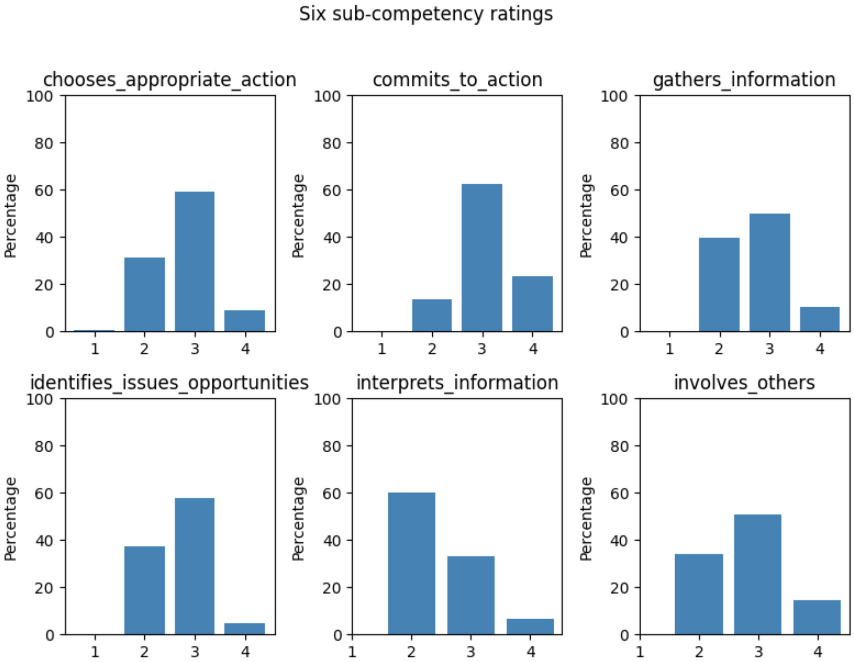
Analysis

Plot the data

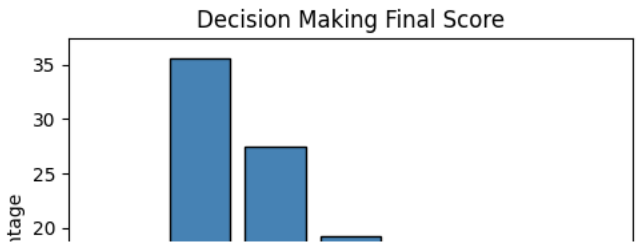
```
# How long are the responses
data["all_text_clean"].apply(lambda x: len(str(x).split())).describe()
```

```
count    1466.000000
mean     1071.603001
std       502.849520
min       162.000000
25%       714.250000
50%      1006.000000
75%      1342.000000
max      4876.000000
Name: all_text_clean, dtype: float64
```

```
# Plot the six indicator ratings
ratings_columns = [col for col in data.columns if col.startswith('rating_')]
ratings_data = data[ratings_columns]
ratings_data.columns = ratings_data.columns.str.replace('rating_', '')

import matplotlib.pyplot as plt

fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(8, 6))

for i, (col, ax) in enumerate(zip(ratings_data.columns[:6], axes.flatten())):
    ax.bar(ratings_data[col].value_counts(normalize=True).sort_index().index,
           ratings_data[col].value_counts(normalize=True).sort_index() * 100,
           color='steelblue')
    ax.set_title(col)
    ax.set_ylabel('Percentage')
    ax.set_xticks([1,2,3,4])
    ax.set_ylim(0,100)

plt.suptitle('Six sub-competency ratings', y=1.02)
plt.tight_layout()
plt.show()
```




```
# Plot the distribution of overall decision-making score
fig, ax = plt.subplots(figsize=(5, 4))

ax.bar(ratings_data['decision_making_final_score'].value_counts(normalize=True).sort_index().index,
       ratings_data['decision_making_final_score'].value_counts(normalize=True).sort_index() * 100,
       color = 'steelblue', edgecolor = 'black')
ax.set_title('Decision Making Final Score', fontsize = 12)
ax.set_ylabel('Percentage', fontsize = 10)
ax.set_xlabel('Rating', fontsize = 10)
ax.set_xticks(list(range(1,8)))
ax.tick_params(axis='both', which='both', labelsize=10)

plt.tight_layout()
plt.show()
```



Analysis

Pre-Trained Models

Load three pre-trained word embedding models.

Word2Vec model: trained on a large corpus of Google News articles, this model contains 300-dimensional vectors for 3 million words and phrases (Mikolov et al., 2013) https://arxiv.org/abs/1310.4546

GloVe model: trained on the 6 billion tokens from the English language Wikipedia and the Gigaword5 dataset (https://catalog.ldc.upenn.edu/LDC2011T07), this model contains 300-dimensional vectors (Pennington, Socher and Manning 2014).

Fasttest model: trained on Wikipedia 2017, UMBC webbase corpus, and statmt.org news dataset (16B tokens), comprises 1 million 300-dimensional word vectors https://fasttext.cc/docs/en/english-vectors.html

```
from gensim.models import Word2Vec
import gensim.downloader as api

# Load a pre-trained Word2Vec model (e.g., 'word2vec-google-news-300')
#pretrained_model = api.load('word2vec-google-news-300')


# Save the model for easier loading next time
#pretrained_model.save(f'{file_path}pretrained_w2v_google300')


# load a saved pretrained model
from gensim.models import KeyedVectors
pretrained_model = KeyedVectors.load(f'{file_path}pretrained_w2v_google300', mmap='r')
```

```
type(pretrained_model)
```

```
    gensim.models.keyedvectors.KeyedVectors
```

```
pretrained_model.__contains__("database")
```

```
    True
```

```
pretrained_model.similarity("careful", "cautious")
```

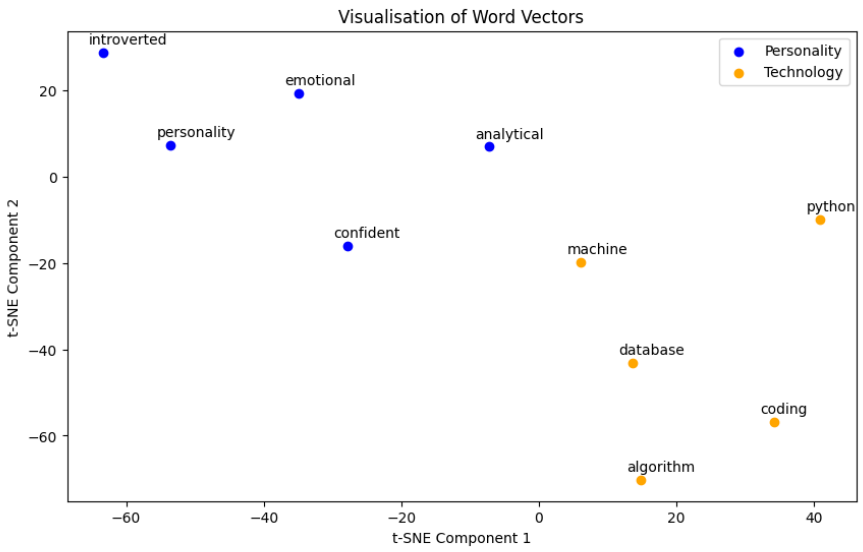
```
    0.64839727
```

```
# Load a pretrained GloVe word embeddings model
#pretrained_model_glove = api.load("glove-wiki-gigaword-300")


# Save the model for easier loading next time
#pretrained_glove.save(f'{file_path}pretrained_glove_wiki300')


# Load the model from the file
pretrained_glove = KeyedVectors.load(f'{file_path}pretrained_glove_wiki300', mmap='r')


# Load a pretrained Fastext subword embeddings model
#pretrained_fasttext = api.load("fasttext-wiki-news-subwords-300")


# Save the model for easier loading next time
#pretrained_fasttext.save(f'{file_path}pretrained_fasttext300')


# Load the model from the file
pretrained_fasttext = KeyedVectors.load(f'{file_path}pretrained_fasttext300', mmap='r')
```

Visualisation of word vectors for demonstration

Use t-SNE to visualise high-dimensional vectors in low-dimensional space.

```
from sklearn.manifold import TSNE
import numpy as np

# Sample of words related to personality and technology
personality_words = ["emotional", "introverted", "confident", "analytical", "personality"]
tech_words = ["algorithm", "machine", "database", "python", "coding"]
sample_words = personality_words + tech_words

# Word vectorisation using pre-trained w2v model
sample_vectors = [pretrained_model[word] for word in sample_words if word in pretrained_model]
sample_vectors = np.array(sample_vectors)

# Dimensionality reduction using t-SNE
tsne_model = TSNE(n_components=2, perplexity=5, random_state=10)
tsne_result = tsne_model.fit_transform(sample_vectors)

# Plot results
plt.figure(figsize=(10, 6))

plt.scatter(tsne_result[:5, 0], tsne_result[:5, 1], color='blue', label='Personality')
plt.scatter(tsne_result[5:, 0], tsne_result[5:, 1], color='orange', label='Technology')

# Annotate each point with the corresponding word
for i, word in enumerate(sample_words):
    plt.annotate(word, (tsne_result[i, 0] - 2, tsne_result[i, 1] + 2))

plt.xlabel('t-SNE Component 1')
plt.ylabel('t-SNE Component 2')
plt.title('Visualisation of Word Vectors')
plt.legend()

plt.show()
```



Similarity metrics

Cosine similarity and 1- Word Mover's Distance (WMD) are used to calculate similarity between the word embedding vectors. Two variations of Cosine similarity are calculated based on different representations of the text. As WMD measures distance betwen vectors, the value is multiplied by -1 to provide a similarity score.

The three described similarity scores are calculated for each of the pre-trained word embedding models, totalling six similarity scores to be evaluated.

```
from sklearn.metrics.pairwise import cosine_similarity

# Function to calculate cosine similarity between two texts (average vectors)
def calculate_cosine_similarity(text1, text2, nlp_model):
    text1_vectors = [nlp_model[word] for word in text1 if word in nlp_model]
    text2_vectors = [nlp_model[word] for word in text2 if word in nlp_model]

    if not text1_vectors or not text2_vectors:
        return 0.0  # Handle cases where there are no word vectors available

    # Calculate the mean vectors for text1 and text2
    mean_vector1 = np.mean(text1_vectors, axis=0)
    mean_vector2 = np.mean(text2_vectors, axis=0)

    # Calculate cosine similarity between the mean vectors
    similarity = cosine_similarity([mean_vector1], [mean_vector2])

    return similarity[0][0]  # Return the similarity score


from scipy.spatial import distance

# Function to calculate Euclidean distance between two texts (average vectors)
def euclidean_distance(text1, text2, nlp_model):
    text1_vectors = [nlp_model[word] for word in text1 if word in nlp_model]
    text2_vectors = [nlp_model[word] for word in text2 if word in nlp_model]

    if not text1_vectors or not text2_vectors:
        return 0.0  # Handle cases where there are no word vectors available

    # Calculate the mean vectors for text1 and text2
    mean_vector1 = np.mean(text1_vectors, axis=0)
    mean_vector2 = np.mean(text2_vectors, axis=0)

    # Calculate negative Euclidean distance between the mean vectors
    similarity = - distance.euclidean(mean_vector1, mean_vector2)

    return similarity  # Return the similarity score
```

For each word embedding model, calculate semantic similarity between all texts and the target text using the three similarity metrics

```
# Cosine similarity
data['sim_w2v_cosine'] = data['tokenized_text'].apply(lambda x: calculate_cosine_similarity(x, target_text_tokens, pretraine
data['sim_glove_cosine'] = data['tokenized_text'].apply(lambda x: calculate_cosine_similarity(x, target_text_tokens, pretrai
data['sim_fast_cosine'] = data['tokenized_text'].apply(lambda x: calculate_cosine_similarity(x, target_text_tokens, pretrain


# Euclidean similarity
data['sim_w2v_euclidean'] = data['tokenized_text'].apply(lambda x: euclidean_distance(x, target_text_tokens, pretrained_mode
data['sim_glove_euclidean'] = data['tokenized_text'].apply(lambda x: euclidean_distance(x, target_text_tokens, pretrained_gl
data['sim_fast_euclidean'] = data['tokenized_text'].apply(lambda x: euclidean_distance(x, target_text_tokens, pretrained_fas


# Negative Word Mover's Distance
data['sim_w2v_wmd'] = data['tokenized_text'].apply(lambda x: - pretrained_model.wmdistance(x, target_text_tokens))
data['sim_glove_wmd'] = data['tokenized_text'].apply(lambda x: - pretrained_glove.wmdistance(x, target_text_tokens))
data['sim_fast_wmd'] = data['tokenized_text'].apply(lambda x: - pretrained_fasttext.wmdistance(x, target_text_tokens))
```

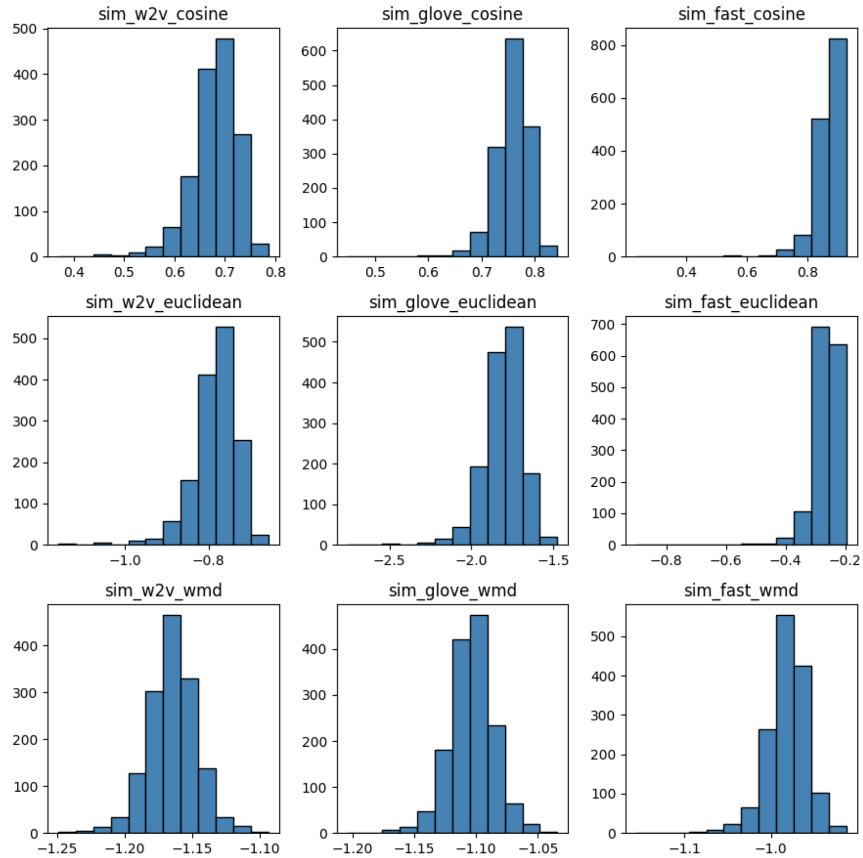
Evaluate the results

```
summary_statistics = data.filter(regex='^sim').describe()
print(summary_statistics)
```

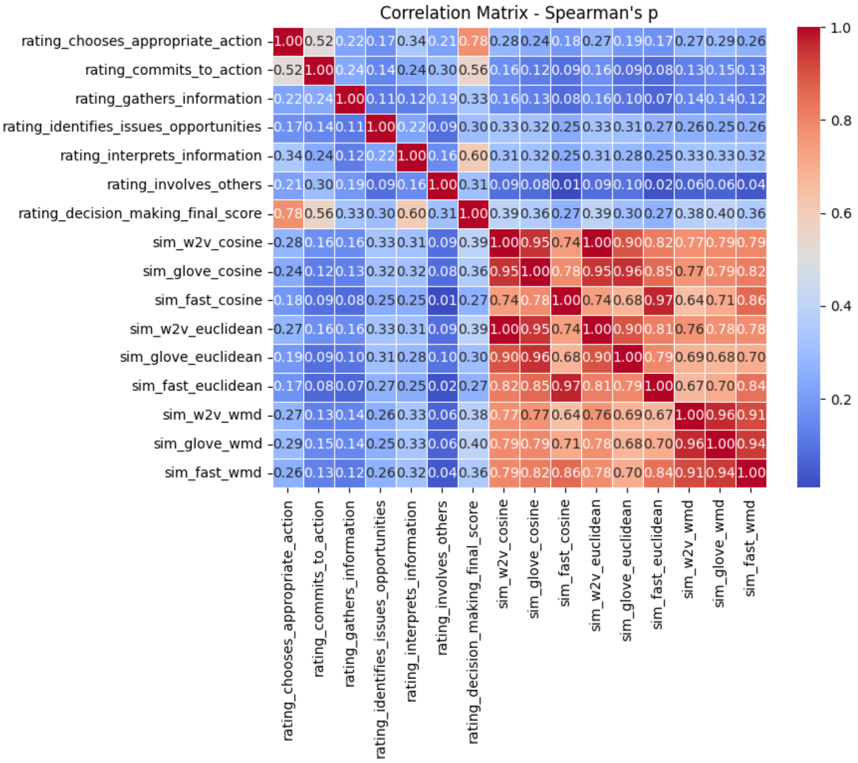
```
       sim_w2v_cosine  sim_glove_cosine  sim_fast_cosine  sim_w2v_euclidean  \
count     1466.000000       1466.000000      1466.000000        1466.000000
mean         0.679288          0.757767         0.866365          -0.783799
std          0.046193          0.033405         0.045430           0.052404
min          0.368812          0.446742         0.235892          -1.159337
25%          0.656016          0.740748         0.853249          -0.809079
50%          0.684640          0.761566         0.876094          -0.777987
75%          0.711387          0.779749         0.892887          -0.748503
max          0.786198          0.843556         0.928998          -0.657482

       sim_glove_euclidean  sim_fast_euclidean  sim_w2v_wmd  sim_glove_wmd  \
count          1466.000000         1466.000000  1466.000000    1466.000000
mean             -1.804743           -0.267424    -1.164372      -1.103552
std               0.120192            0.044425     0.018223       0.018320
min              -2.759786           -0.901615    -1.249136      -1.204662
25%              -1.869076           -0.282924    -1.175132      -1.114076
```

```
50%              -1.794820           -0.259362    -1.164162      -1.103148
75%              -1.725815           -0.240347    -1.153584      -1.092321
max              -1.473343           -0.196005    -1.093201      -1.034004

       sim_fast_wmd
count   1466.000000
mean      -0.981309
std        0.022887
min       -1.155438
25%       -0.993617
50%       -0.980046
75%       -0.967153
max       -0.912803
```

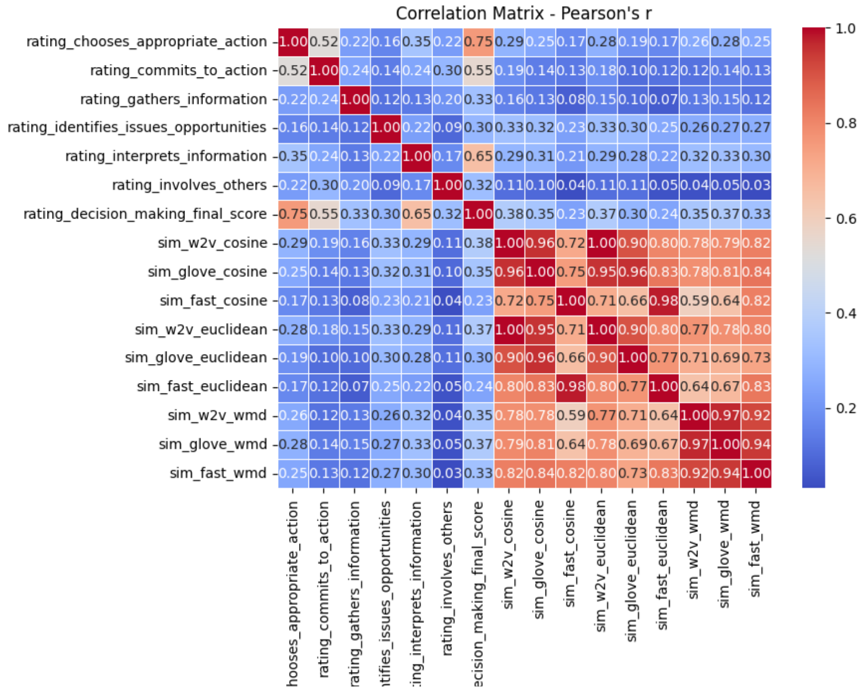
```
# Select the scores with column names starting with 'sim_'
sim_scores = data.filter(regex='^sim_')

# Create a 3x3 grid plot
fig, axes = plt.subplots(3, 3, figsize=(9,9))

# Flatten the 2D array of subplots for easier iteration
axes = axes.flatten()

# Plot each histogram
for i, col in enumerate(sim_scores.columns):
    axes[i].hist(sim_scores[col], bins=12, color='steelblue', edgecolor='black')
    axes[i].set_title(col)

# Adjust layout
plt.tight_layout()
plt.show()
```



```
# Plot relationship between all ratings and similarity scores - Non-parametric Spearman's rho
import seaborn as sns

# Exclude non-numeric columns
numeric_data = data[data['text_exercise_final_clean'].str.strip() != ""].select_dtypes(include='number')

# Calculate the correlation matrix
correlation_matrix = numeric_data.corr(method = 'spearman')

# Create a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm', linewidths=0.5)
plt.title("Correlation Matrix - Spearman's p")
plt.show()
```




```
# Plot relationship between all ratings and similarity scores - Pearson's r

# Calculate the correlation matrix
correlation_matrix = numeric_data.corr(method = 'pearson')

# Create a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm', linewidths=0.5)
plt.title("Correlation Matrix - Pearson's r")
plt.show()
```

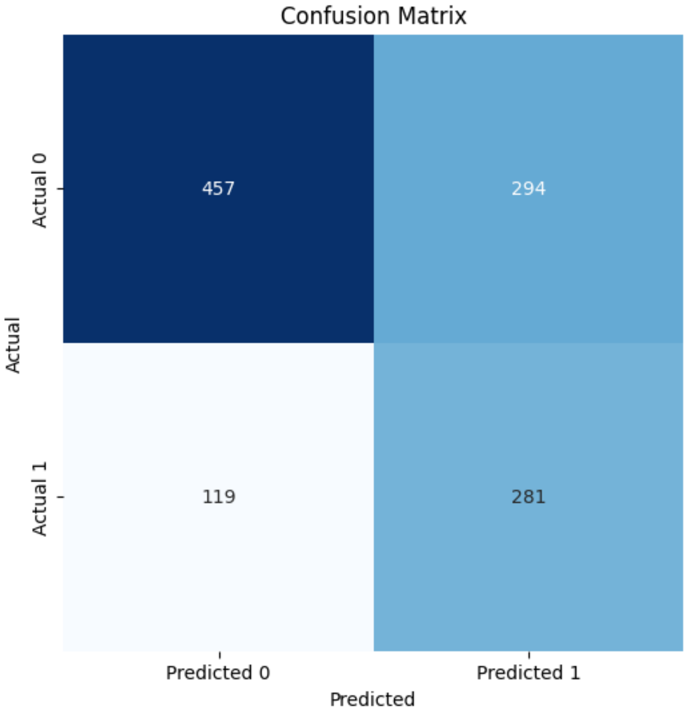


Evaluation metrics

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, confusion_matrix

model_names = ['w2v_cosine', 'w2v_euclidean', 'w2v_wmd', 'glove_cosine', 'glove_euclidean', 'glove_wmd', 'fast_cosine', 'fas

metrics_dict = {'Model': [], 'Accuracy': [], 'Precision': [], 'Recall': [], 'F1 Score': [], 'ROC-AUC': []}

# Convert to binary
numeric_data['human_binary'] = (numeric_data['rating_decision_making_final_score'] > 3.5).astype(int)
for model_name in model_names:
   numeric_data[f'bin_{model_name}'] = (numeric_data[f'sim_{model_name}'] > numeric_data[f'sim_{model_name}'].median()).asty
   #numeric_data[f'bin_{model_name}'] = (numeric_data[f'sim_{model_name}'] > .5).astype(int)

# Evaluate each model
for model_name in model_names:
    # Get predictions for the current model
    predictions = numeric_data[f'bin_{model_name}']
    # Actual y values
    human_binary = numeric_data['human_binary']

    # Calculate metrics
    accuracy = accuracy_score(human_binary, predictions)
    precision = precision_score(human_binary, predictions)
    recall = recall_score(human_binary, predictions)
    f1 = f1_score(human_binary, predictions)
    roc_auc = roc_auc_score(human_binary, predictions)

    # Update the metrics dictionary
    metrics_dict['Model'].append(model_name)
    metrics_dict['Accuracy'].append(accuracy)
    metrics_dict['Precision'].append(precision)
    metrics_dict['Recall'].append(recall)
    metrics_dict['F1 Score'].append(f1)
    metrics_dict['ROC-AUC'].append(roc_auc)

# Create a DataFrame from the metrics dictionary
metrics_df = pd.DataFrame(metrics_dict)

# Display the table
print(metrics_df)
```

```
              Model  Accuracy  Precision  Recall  F1 Score   ROC-AUC
0        w2v_cosine  0.639444   0.486957  0.7000  0.574359  0.653595
1     w2v_euclidean  0.637706   0.485217  0.6975  0.572308  0.651679
2           w2v_wmd  0.641182   0.488696  0.7025  0.576410  0.655511
3      glove_cosine  0.625543   0.473043  0.6800  0.557949  0.638269
4   glove_euclidean  0.611642   0.459130  0.6600  0.541538  0.622943
5         glove_wmd  0.641182   0.488696  0.7025  0.576410  0.655511
6       fast_cosine  0.609904   0.457391  0.6575  0.539487  0.621027
7    fast_euclidean  0.608167   0.455652  0.6550  0.537436  0.619111
8          fast_wmd  0.622068   0.469565  0.6750  0.553846  0.634437
```

```
y_true = numeric_data['human_binary']
y_pred = numeric_data['bin_glove_wmd']

# Create confusion matrix
conf_matrix = confusion_matrix(y_true, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



```
model_names = ['w2v_cosine', 'w2v_euclidean', 'w2v_wmd', 'glove_cosine', 'glove_euclidean', 'glove_wmd', 'fast_cosine', 'fas

model_names = ['rating_gathers_information']


metrics_dict = {'Model': [], 'Accuracy': [], 'Precision': [], 'Recall': [], 'F1 Score': [], 'ROC-AUC': []}

for model_name in model_names:
    # Get predictions for the current model
    #predictions = (numeric_data[f'sim_{model_name}'] > numeric_data[f'sim_{model_name}'].quantile(0.33)).astype(int)
    predictions = (numeric_data[f'{model_name}'] > 2.5).astype(int)

    # Actual y values
    human_binary = (numeric_data['rating_decision_making_final_score'] > 3.5).astype(int)

    # Calculate metrics
    accuracy = accuracy_score(human_binary, predictions)
    precision = precision_score(human_binary, predictions)
    recall = recall_score(human_binary, predictions)
    f1 = f1_score(human_binary, predictions)
    roc_auc = roc_auc_score(human_binary, predictions)

    # Update the metrics dictionary
    metrics_dict['Model'].append(model_name)
    metrics_dict['Accuracy'].append(accuracy)
    metrics_dict['Precision'].append(precision)
    metrics_dict['Recall'].append(recall)
    metrics_dict['F1 Score'].append(f1)
    metrics_dict['ROC-AUC'].append(roc_auc)

# Create a DataFrame from the metrics dictionary
metrics_df = pd.DataFrame(metrics_dict)

# Display the table
print(metrics_df)
```

```
                        Model  Accuracy  Precision  Recall  F1 Score   ROC-AUC
0  rating_gathers_information  0.590791   0.449788   0.795  0.574526  0.638512
```

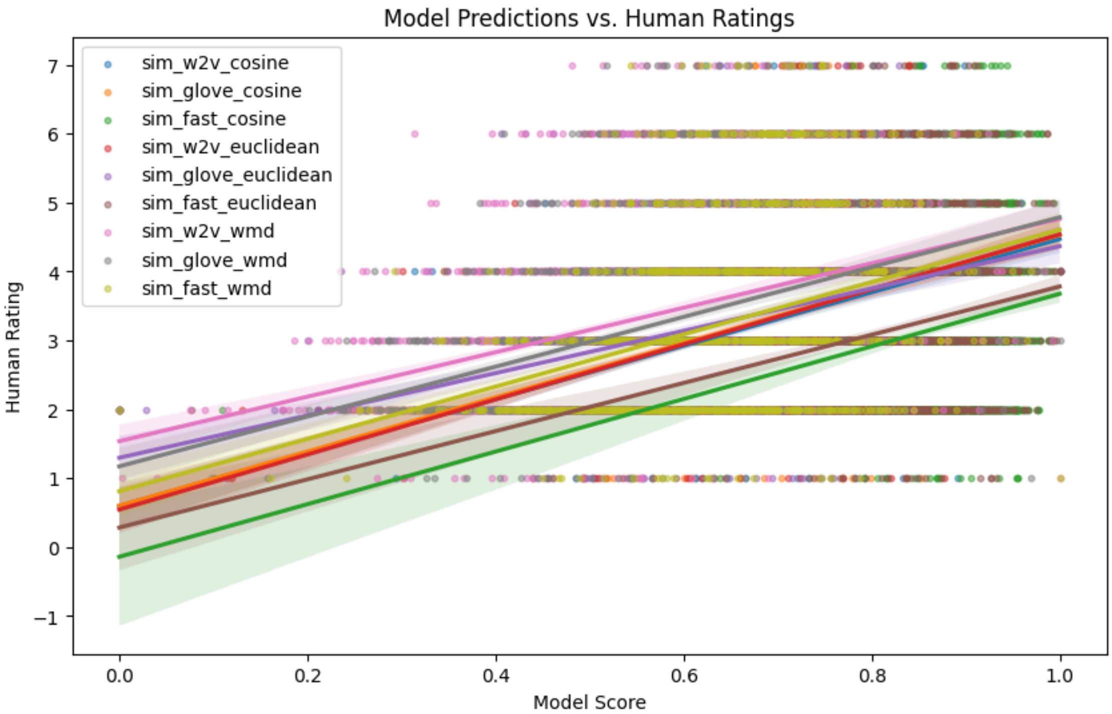
```
model_names = ['w2v_cosine', 'w2v_euclidean', 'w2v_wmd', 'glove_cosine', 'glove_euclidean', 'glove_wmd', 'fast_cosine', 'fast

metrics_dict = {'Model': [], 'Accuracy': [], 'Precision': [], 'Recall': [], 'F1 Score': [], 'ROC-AUC': []}

for model_name in model_names:
    # Get predictions for the current model
    #predictions = (numeric_data[f'sim_{model_name}'] > numeric_data[f'sim_{model_name}'].quantile(0.33)).astype(int)
    predictions = (numeric_data[f'sim_{model_name}'] > .6).astype(int)

    # Actual y values
    human_binary = (numeric_data['rating_decision_making_final_score'] > 3.5).astype(int)

    # Calculate metrics
    accuracy = accuracy_score(human_binary, predictions)
    precision = precision_score(human_binary, predictions)
    recall = recall_score(human_binary, predictions)
    f1 = f1_score(human_binary, predictions)
    roc_auc = roc_auc_score(human_binary, predictions)

    # Update the metrics dictionary
    metrics_dict['Model'].append(model_name)
    metrics_dict['Accuracy'].append(accuracy)
    metrics_dict['Precision'].append(precision)
    metrics_dict['Recall'].append(recall)
    metrics_dict['F1 Score'].append(f1)
    metrics_dict['ROC-AUC'].append(roc_auc)

# Create a DataFrame from the metrics dictionary
metrics_df = pd.DataFrame(metrics_dict)

# Display the table
print(metrics_df)
```

```
             Model  Accuracy  Precision  Recall  F1 Score   ROC-AUC
0       w2v_cosine  0.364031   0.352837   0.995  0.520942  0.511481
1    w2v_euclidean  0.652476   0.000000   0.000  0.000000  0.500000
2          w2v_wmd  0.652476   0.000000   0.000  0.000000  0.500000
3     glove_cosine  0.347524   0.347524   1.000  0.515796  0.500000
4  glove_euclidean  0.652476   0.000000   0.000  0.000000  0.500000
5        glove_wmd  0.652476   0.000000   0.000  0.000000  0.500000
6      fast_cosine  0.349262   0.348129   1.000  0.516462  0.501332
7   fast_euclidean  0.652476   0.000000   0.000  0.000000  0.500000
```

```
8        fast_wmd  0.652476   0.000000   0.000  0.000000  0.500000
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision is il
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision is il
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision is il
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision is il
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision is il
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision is il
  _warn_prf(average, modifier, msg_start, len(result))
```

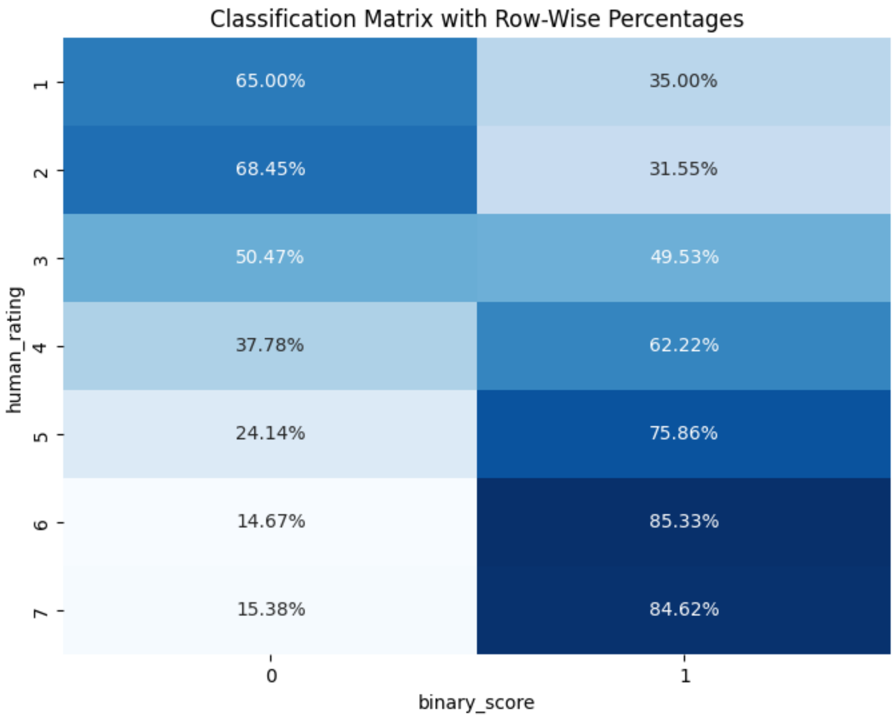
```
# Rescale all similarity scores to 0-1
from sklearn.preprocessing import MinMaxScaler

sim_columns = numeric_data.filter(regex='^sim_')
numeric_data.loc[:, sim_columns.columns] = MinMaxScaler().fit_transform(sim_columns)
```

```
# Create a single plot with regression lines for each predictor
fig, ax = plt.subplots(figsize=(10, 6))
for predictor in sim_columns.columns:
    sns.regplot(data=numeric_data, x=predictor, y='rating_decision_making_final_score', scatter=True, label=predictor, scatt

ax.set_title('Model Predictions vs. Human Ratings', fontsize = 12)
ax.set_ylabel('Human Rating', fontsize = 10)
ax.set_xlabel('Model Score', fontsize = 10)

plt.legend()
plt.show()
```



```python
df = numeric_data[['rating_decision_making_final_score', 'sim_glove_wmd']]

# Define a function to convert values to binary based on median
def convert_to_binary(value, median):
    return 1 if value >= median else 0

# Calculate the median for "rating" and "score" columns
#median_rating = df['rating_decision_making_final_score'].median()
median_rating = 3.5
median_score = df['sim_glove_wmd'].median()

# Convert "rating" and "score" to binary columns based on median
df['human_binary'] = df['rating_decision_making_final_score'].apply(lambda x: convert_to_binary(x, median_rating))
df['human_rating'] = df['rating_decision_making_final_score']
df['binary_score'] = df['sim_glove_wmd'].apply(lambda x: convert_to_binary(x, median_score))

# Compute the confusion matrix
confusion_matrix = pd.crosstab(df['human_rating'], df['binary_score'], normalize='index')  # Normalise along rows

# Create a heatmap to visualise the confusion matrix with row-wise percentages
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_matrix, annot=True, fmt=".2%", cmap="Blues", cbar=False)  # Format as percentages
plt.title('Classification Matrix with Row-Wise Percentages')
plt.show()
```

```
<ipython-input-52-c1b370df5e80>:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-
  df['human_binary'] = df['rating_decision_making_final_score'].apply(lambda x: convert_to_binary(x, median_rating))
<ipython-input-52-c1b370df5e80>:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-
  df['human_rating'] = df['rating_decision_making_final_score']
<ipython-input-52-c1b370df5e80>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-
  df['binary_score'] = df['sim_glove_wmd'].apply(lambda x: convert_to_binary(x, median_score))
```



```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, roc_curve, auc
```